Summer Optimization Workshop

Department of Mathematics
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Schedule on July 30, 2026. Place: M212, Mathematics Building

	Speaker	Title	Chair
09:20 | 09:40	Alper Yildirim	Simplicial quadratic optimization problems, conic duality and attainability	Yu-Lin Chang
09:40 | 10:00	Rabian Wangkeeree	A Neurodynamic Framework for Generalized Pinball-Loss SVMs: Admissible Smoothings, Provable Convergence, and an MRI Bone-Density Application	Yu-Lin Chang
10:00 | 10:20	Kasamsuk Ungchittrakool	A Projection-Based Neurodynamic Approach to l_1-Regularized Optimization: Stability and Applications	Yu-Lin Chang
10:20 | 10:40	*Tea Break*		
10:40 | 11:00	Thanatporn Grace	A Fully Smooth Neural Network for Nonlinear Semidefinite Programming via Smoothed Fischer–Burmeister Functions	Ching-Yu Yang
11:00 | 11:20	Nutt Tananimit	Fixed-Time Stability and Noise Robustness of a Polynomial-Gain Gradient Neural Network for Absolute Value Equations	Ching-Yu Yang
11:20 | 11:40	Yirga Abebe Belay	Approximating Solutions of Generalized Pinball Probabilistic Support Vector Machines using Neural Networks with Smoothing Techniques	Ching-Yu Yang
11:40 | 12:00	*Free Discussion*		

Simplicial quadratic optimization problems, conic duality and attainability

Alper Yildirim

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Abstract

We are interested in exactness, strong conic duality and dual attainability in copositive relaxations of quadratic optimization problems (QPs) of a special form, in which any (feasible) QP can be recast. By using our results, the celebrated Frank-Wolfe theorem on the attainability of any bounded QP even over unbounded polyhedra, regardless of whether the objective function is convex or not, follows very easily.

This is joint work with Immanuel Bomze.

A Neurodynamic Framework for Generalized Pinball-Loss SVMs: Admissible Smoothings, Provable Convergence, and an MRI Bone-Density Application

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Abstract

We extend the neurodynamical neural network for the generalized pinball-loss support vector machine (GPL–SVM) from a single hyperbolic-tangent smoothing to a *smoothing-function-agnostic* model, the GS–GPIN–SVM. For an entire *admissible class* of smoothings of the plus function we establish existence, uniqueness, and—through a single composite Lyapunov function—global asymptotic and global exponential stability of the equilibrium, together with exponential decay of the observable optimality residual $\|\nabla G(\omega(t))\| = \|\dot{\omega}(t)\| / \kappa$. Within this class we isolate two compactly supported polynomial smoothings—the Zang (C^1) and Ye–Liu–Zhou–Liu (C^2) functions—yielding the CS–GPIN–SVM, which recovers the GPL exactly outside a vanishing band, uses only elementary arithmetic, and delivers true sparsity. We further prove a uniform approximation-error bound and a gradient-consistency theorem: as the smoothing parameter tends to infinity, the network equilibria converge to the global minimiser of the exact non-smooth GPL–SVM. Experiments on synthetic, six UCI, and large-scale benchmarks confirm the theory—the compact smoothings attain the smallest approximation error, the highest sparsity, and the best tuned accuracy rank—and an MRI-based bone-mineral-density feasibility study ($n = 194$) shows a class-balanced RBF variant competitive with strong classical and deep-learning baselines.

Key contributions

- **Unified theory.** One admissibility definition covers global (tanh, sigmoid, erf, ...) and compactly supported smoothings under a single convergence and stability analysis.
- **Composite-Lyapunov stability.** A single Lyapunov function controls the state error *and* the optimality residual, giving global exponential stability for the whole class (including the C^1 Zang smoothing) and a sharper asymptotic rate for the C^2 members.
- **Exactness and sparsity.** Compact smoothings reproduce the generalized pinball loss outside a vanishing band, using only elementary arithmetic and yielding genuinely sparse models.
- **Real-world application.** An MRI-based bone-mineral-density study ($n = 194$) demonstrates clinical feasibility against classical and deep-learning baselines.

Keywords: Generalized pinball loss; Neurodynamic neural networks; Smoothing functions; Gradient consistency; Support vector machines; Lyapunov stability; GS–GPIN–SVM; CS–GPIN–SVM.

A Projection-Based Neurodynamic Approach to l_1-Regularized Optimization: Stability and Applications

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Abstract

Sparse optimization problems, particularly the l_1-regularized least squares problem (LASSO), lie at the heart of modern signal processing and data science. Recurrent neural network (RNN) based solvers have emerged as an attractive framework for these problems owing to their inherent parallelism and real-time capability. However, most existing neurodynamic models handle the non-smooth l_1 penalty by decomposing each variable into its positive and negative components, which doubles the problem dimension and incurs unnecessary computational overhead. In this talk, we introduce an efficient one-layer recurrent neural network that directly solves the LASSO problem in its original variable space. The key idea is to exploit a Prox-Projection identity that replaces the l_1 subgradient with a simple projection operator, thereby completely eliminating the need for variable splitting. The resulting architecture is substantially simpler and more memory-efficient than its dimension-doubling counterparts. We prove that the proposed network is globally asymptotically stable under general conditions and globally exponentially stable when the objective satisfies a strong convexity assumption. Numerical experiments on image restoration confirm the theoretical findings, showing competitive accuracy with markedly improved computational efficiency.

Keywords: LASSO, l_1-Regularization, Projection Neural Network, Recurrent Neural Network, Lyapunov Stability, Sparse Optimization.

References

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A Fully Smooth Neural Network for Nonlinear Semidefinite Programming via Smoothed Fischer–Burmeister Functions

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Abstract

We propose a fully smooth continuous-time neural network for solving convex nonlinear semidefinite programming (NSDP) problems with both matrix inequality and scalar inequality constraints. Both constraint types are handled through smoothed Fischer–Burmeister (FB) functions: the matrix-valued extension Φ_μ is used for the linear matrix inequality (LMI), and the scalar smooth FB function ϕ_μ is applied componentwise to the inequality constraints. The resulting energy function $E(y) = \frac{1}{2}\|\eta_\mu(y)\|^2$ is C^∞ for every $\mu > 0$, which yields a Lipschitz right-hand side and guarantees global existence and uniqueness of solution trajectories. We prove that every equilibrium of the network coincides with a KKT point of the NSDP and that the network is globally asymptotically stable. Numerical experiments on standard NSDP benchmark problems confirm that the proposed architecture converges from arbitrary initial conditions and achieves competitive performance against existing projection-based neural network methods.

Keywords: Fischer–Burmeister function, global stability, KKT conditions, neural network, nonlinear semidefinite programming, smoothing method, Lyapunov stability.

Fixed-Time Stability and Noise Robustness of a Polynomial-Gain Gradient Neural Network for Absolute Value Equations

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Abstract

In this paper, we propose a Fixed-time Gradient Neural Network (FGNN) for solving the absolute value equation $Ax - |x| = b$. The FGNN employs a polynomial-gain architecture that combines sub-linear, super-linear, and reciprocal damping terms. We prove global fixed-time stability of the unperturbed system with an explicit settling-time bound and establish four robustness theorems: fixed-time stability and fixed-time boundedness under both bounded vanishing and bounded non-vanishing noise. Numerical experiments across nine models spanning three reformulation families validate FGNN's fixed-time convergence, dual noise robustness, and practical efficacy. A limitation analysis of the exponential predefined-time gain reveals catastrophic floating-point overflow at moderate initial residuals, further motivating the polynomial-gain design as a numerically reliable alternative with rigorous theoretical guarantees.

Keywords: Fixed-time stability; Gradient neural networks; Absolute value equations; Polynomial-gain architecture; Noise robustness; Non-vanishing perturbations; Lyapunov stability; Predefined-time limitations.

Approximating Solutions of Generalized Pinball Probabilistic Support Vector Machines using Neural Networks with Smoothing Techniques

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Abstract

We propose a neurodynamical neural network method for solving machine learning algorithms, specifically, the probabilistic Support Vector Machines (SVMs) involving different smoothing techniques of generalized pinball loss function. First, we employ seven different smoothing functions which approximate the non-smooth generalized pinball loss function associated with the probabilistic SVM problem. Next we propose a gradient neural network model to find real-time solutions of the probabilistic SVM with smooth objective function. We prove the relation between the optimal solutions of the smoothed problem and the equilibrium points of the proposed dynamical system. We then analyze existence and uniqueness properties of the introduced model followed by Lyapunov and asymptotic stability analysis. We next provide numerical experiments on synthetic and UCI benchmark to guarantee the effectiveness of the proposed model using the performance metrics: Accuracy, MCC, and F1-score. Finally, we compare the effectiveness of the proposed method with four benchmark methods.

Keywords: Generalized pinball loss; Global convergence; Neural networks; Probabilistic support vector machines; Smoothing functions; Stability.